

***Do Loss Leader Promotions Impact Store Profits? :
An Empirical Investigation for Grocery Industry***

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ABSTRACT

Despite the widespread popularity of loss leader promotions, there have been very few systematic empirical studies about its impact on store performance. In this study, we use detailed transaction data from multiple stores of a grocery supermarket chain to estimate: (1) the overall impact of loss leader promotion strategy on store profits; (2) the relative effectiveness of different product categories as loss leaders; and (3) the optimal levels of loss leader promotions in terms of improving overall store profits. The aggregate level analyses show that the “breadth” of store-wide loss leader promotion is most likely to induce increased store traffic, while its “depth” leads to higher sales per customer and higher margins. This result indicates that the deep discounts are more successful at attracting large basket customers who also buy items that are not discounted. We find that store profits increase between 0.7 and 9.8 percent due to loss leaders. The disaggregate level analyses reveal marked differences across product categories in their relative effectiveness as loss leaders in boosting store profit. We show how our results can be used by retailers to further improve overall store profits through loss leader promotions by reallocating promotion intensities across different categories.

INTRODUCTION

Product promotions are an important element of competitive dynamics in retail markets with retailers using a myriad of promotion techniques to attract consumers. Some of the most commonly used techniques are the typical price cuts, “loss leader” promotions (deep discount or attention grabber promotions), feature advertising (store flyers), and in-store displays. According to the *Promotion Marketing Association*, the total promotion spending across all product categories in the USA reached \$429 billion (about 3.65 % of the GDP) in 2004. Given the widespread use of retail promotions and the magnitude of the dollars spent on them, managers and academicians have a great interest in understanding how consumers react to such promotions and how that affects retailers’ performance (Ailawadi et al. 2006; Inman and McAlister 1993; McAlister, George, and Chien 2008; Raghurir, Inman, and Grande 2004). In this paper, our focus is on loss leader and feature promotion strategies in the grocery retail industry, which represents an annual market size of about half a trillion dollars in the USA and accounts for a significant part of household consumption expenditure (US Census Bureau 2006). Based on a recent estimate by *A.C. Nielsen* (2007), promotional sales accounted for as much of 36 % of all grocery sales in the USA.

Most of the theoretical literature in pricing is typically based on the premise that firms sell only one or two products (Lal and Matutes 1994; Rao and Syam 2001; Shaffer and Zhang 2002). However, in empirical reality such an assumption represents a gross simplification of the actual product portfolios for most retailers, especially of grocery products. Recognition of such ubiquitous multi-product assortments offered by retailers allows for a deeper understanding of the motives and opportunities for strategic pricing by retailers. For instance, a large assortment of products presents retailers the potential to cross-subsidize and engage in interesting price

promotion strategies that many not be possible with one or two products situations. One particularly popular price promotion strategy in that vein is the so called “loss leader” promotion strategy (Bliss 1988; Drèze 1995; Lal and Matutes 1994; Walters and MacKinzie 1988).

The loss leader promotion strategy is distinct from other retailer price promotion strategies in that the prices for the selected loss leader items are set at or below retailers’ respective marginal costs. A recent NY Times article¹ describes loss leader promotions as “*Loss leaders are called that because by selling items at a loss or even giving them away, stores can lure in shoppers who will buy other, more profitable items*”. In other words, retailers consciously incur loss or earn no profit on the sale of these items. The rationale being that such deep price discounts on the loss leader items will lead to increased customer traffic for the promoting store. And since there are economies of scale in shopping, once at the store, customers would often buy items other than which are on loss leader promotion. So, the eventual expectation is that the negative contribution from the loss-leader items bought by the customers will be more than offset by the profit generated from the sale of non-loss-leader items to them (Duncan, Hollander and Savit 1984; Hess and Gerstner 1987; Mason and Mayer 1984; Rao and Syam 2001).

Grocery retailers typically promote the loss leader products as “deep discount” deals. These deals are advertised to target consumers through local newspapers, store flyers (feature promotions) and in-store special displays. These advertised deals, constitute an important element of retailer promotion activities (Arnold, Kozinets, and Handelman 2001). They represent about half of retailers’ promotional budgets (Bodapati 1999). These huge budgets are justified by the strategic role attributed to promotion advertisements. In fact, previous research has found that, after controlling for price, advertised price deals *per se* also have considerable effect on influencing brand choice decisions (Chintagunta, Jain and Vilcassim 1991). Of the various

¹ NY Times (August 15, 2008), “Back-to-School Discounts Are Deeper, More Creative.”

forms used to advertise price deals in grocery retail markets, store flyer has been found to be one of the most popular and highly effective in influencing store sales (Gijbrecchts, Campo and Goosens 2003; Mulhern and Leone 1990). *Progressive Grocer Magazine* reports that in 2004 about 71 per cent of the people report to have seen these flyers before shopping. The cover page is the most visible part of store flyer and the items featured on it play a critical role in effecting retailers' performance. So, any systematic analysis to understand the effectiveness of the loss leader promotion strategy on retailers' performance needs to control for the effect of feature promotion of the category at both focal and competitive stores.

Unfortunately, despite the fact that the loss leader promotion strategy is widely prevalent in practice in retail markets, there have been very few systematic empirical studies in terms of its effectiveness on the performance of retailers (Walters and MacKenzie 1988; Walters and Rinne 1986). Even these few empirical studies base their findings on small sample sizes (typically 2-3 stores), and without controlling for the important mediating role of feature promotions of neither focal nor competing stores. So, while conventional wisdom and theoretical studies posit a potential positive role of loss leader promotion strategy on retailer performance, many critical aspects of such role – especially on retailers' profit performance – remain essentially open empirical questions. A major motivation and goal of this study is to undertake a systematic empirical study of the impact of loss leader promotions on different measures (traffic, sales and profit) of store performance in the context of grocery supermarkets. The lack of in-depth past research and importance of the loss leader promotions to retailers make this study particularly timely (Ailawadi et al 2008). We specifically undertake aggregate as well as disaggregate level analyses to address the following issues.

First, a key research issue of interest to retail chain and store managers is the effect of loss-leader promotions at the overall store level on stores' performance measures, especially profit. For instance, how does the "breadth" (% of product items put on loss leader promotion) of loss leader promotion activities in a store affect the store's traffic, sales and profit? Conventional wisdom and economic theory will expect such breadth to have positive impact on store's overall traffic and sales. At the same time, if more and more items are sold at a loss and thus increasing the breadth of loss leader promotion, then the impact on store's overall profit can turn negative. On the other hand, by promoting only a small set of "effective" items in certain categories, store managers can potentially achieve a positive impact of the breadth of loss leader promotion on store profit. A major question for retail managers is thus whether their stores are engaged in too much or too little of loss leader promotion activity. Our aggregate, store level analyses address this question.

Second, the intrinsic heterogeneity in consumer preferences implies that the relative efficacy of loss leader promotion strategy will vary across product items and categories put on loss-leader promotions. So, after gaining insights into the aggregate level effects of loss leader promotion on store performance, the next question of interest to both store and category managers is to identify the relative effectiveness of different product categories as loss leaders on various measures of store performance. We perform disaggregate, category level analyses to address this question.

Finally, we use the findings from our aforesaid aggregate and disaggregate analyses to estimate the optimal levels of loss leader promotions in different product categories and the consequent improvements in store profit compared to the observed levels of promotion and store profit. Taken together, our study presents what we believe to be several key, hitherto unavailable

empirical insights into the impact of supermarket retailers' loss leader promotion strategy on their store performance measures.

The data for our study comes from a large regional U.S. supermarket chain which agreed to collaborate with us for this research. It comprises of all transaction data over 55 weeks across various product categories in 24 stores of the chain. We supplement the transaction data with the weekly store flyer data from both the focal and competing stores. In contrast to the limited past empirical research on loss leader promotions, this allows our analyses to control for feature promotions by both focal and competing stores. Also, it is important to point out that the past research represents the loss leader promotion as a binary variable representing whether an entire category is on promotion or not. This is seldom the case in practice where an entire category is put on a loss leader promotion. Hence, past work suffers from the limitation of not being able to capture the "breadth" or extent of loss leader promotions within a category in constructing a measure of such promotions. We are able to avoid this limitation due to the richness of the data available to us for this study.

The rest of the paper is organized as follows: In the next section, we briefly review the relevant literature in the context of the specific research issues addressed in our study. We then describe our empirical analysis approach followed by a description of the data used to estimate our models. Subsequently, we present the results of our empirical analysis, and then conclude with discussion of our findings and future research directions.

SPECIFIC RESEARCH ISSUES AND RELEVANT LITERATURE

As noted earlier, conventional wisdom underlying the rationale for loss leader promotions is that such "deep discount or attention grabbing" promotions will lead to increased customer traffic for a promoting store. Such increase can come in the form of additional customers

switching stores and/or existing customers making additional store trips. Further expectation is that the lost profit from the loss-leader items bought by the aforesaid customers “lured” into the promoting store will be more than offset by the profit generated from the sale of non-loss-leader items to them.

So, the effectiveness of a retailer’s loss-leader promotion strategy will critically depend on how many of its consumers are attracted by the items put on loss-leader promotion and their typical shopping basket compositions. Given the intrinsic heterogeneity in consumer preferences in terms of their basket compositions as well as in terms of the relative importance of the product categories in the basket, it also implies that the efficacy of loss-leader promotion strategy will vary across product items and categories put on loss-leader promotion. For retail managers, these strategic implications call for empirical insights into a number of research issues with respect to the role of loss-leader promotion strategy in enhancing retailers’ performance. We discuss below several such key research issues by organizing them in terms of levels of data analysis (aggregate and disaggregate) and by focusing on three measures of retail stores’ performance: traffic, sales and profit. We also discuss the relevant existing research and show that its limitations or absence leave these research issues in need of systematic empirical analyses to test for conventional wisdoms and theoretical expectations in some cases, and to shed new insights into essentially open empirical questions in others.

Aggregate-Aggregate Level Analysis

At the aggregate level, a key research issue of interest to retail chain and store managers is the effect of a store’s overall level of loss-leader promotion activities on its performance measures. For instance, how does the “breadth” and “depth” of loss-leader promotion activities in a store affect the store’s traffic, sales and profit? Conventional wisdom and economic theory

will expect them to have a positive impact on the demand generated – thus, on store’s overall traffic and sales. On the other hand, it is expected to influence the store’s overall profit margins negatively. Taken together, the theoretical expectation is that there will be a diminishing return to increased loss leader activity on overall store profits, thereby suggesting the existence of an optimal level of loss leader promotion. That, of course, raises a major strategic question for retail managers: whether their stores are having too much or too little of loss leader promotion activity. In other words, how much more aggregate profit can a store generate by either reducing or increasing its current level of loss leader promotion activities to its optimal level? As it turns out, there has been very little, systematic research on the aggregate level effect of loss leader promotions that can shed insights into this important question for retailers.

Using individual level data from two stores in the home improvement product market, Mulhern and Padgett (1995) find that regular price purchases are highly correlated with promotional price purchases. They find that among shoppers who identify promotions as one of the reasons for visiting the stores, about three quarter of them make regular purchases also. This provides support for the underlying rationale for loss leader promotions – that ‘deep discount’ items may enhance the sale of other items at individual consumer level. At the aggregate store level, Gijsbrechts et al. (2003) find that feature promotions (store flyer size) had a significant impact on store sales in the few stores of their study. In clothing and sporting goods setting, Lam, Vandenbosch, Hulland and Pearce (2001) find that price promotions have a positive impact on store traffic and on the likelihood that a consumer will make a purchase. However, neither of these studies explicitly considered the effect of loss leader promotions nor do they consider the profit measure of store performance.

To the best of our knowledge, the only published study that has investigated the effect of loss leader promotions on aggregate store performance on all the three measures – traffic, sales and profit – is the one by Walters and MacKinzie (1988). Using data from two stores of a chain, they did not find any systematic relationship between aggregate loss leader promotions and overall store profits, but found positive effect on store sales and traffic. However, apart from the limitation of considering only two stores in their study, their analysis also did not consider the mediating impact of the role of feature promotions on store performance. In addition, they did not have any measure of competitive activity, which led them to note that: “*Incorporating measures of competitive activities and including them in future analysis would further add to our knowledge of the effects of retail promotions*”. In contrast, our study will be the first to analyze the effects of loss leader promotions on aggregate store performance measures, including profit, while explicitly considering the mediating role of feature promotions of focal as well as competitive stores. Further, our use of a much larger sample size of 24 stores is likely to provide more generalizable insights about such effects.

Aggregate-Disaggregate Level Analysis

When items in a specific product category are put on loss leader promotion, then the *a priori* expectation would be that the impact on overall store traffic and sales is positive. While the impact on store profit is also desired to be positive by the store manager, whether that is indeed the case will depend on the following underlying consumer behavior dynamics. As noted in Niraj, Padmanabhan and Seetharaman (2008), neoclassical economic theory suggests two opposing ways in which a price cut (or, in our case, loss leader promotion) in one product category could influence buying in a complementary product category: first, by making the focal (i.e., promoted) product category more attractive for current consumption, the price cut induces

the consumer to purchase the product, which then renders a complementary product to be more attractive since the consumer gains additional satisfaction from consuming the two products jointly. This is called the *complementarity effect*. Second, since the focal product in some category is cheaper on account of the loss leader promotion, the consumer may stockpile the product (by buying additional units of the product), which then leads to decreased money available to spend on other product categories that belong to the same “mental account” of the consumer (Thaler 1985). This is called the *expenditure effect*.

Hence, the net effect of loss leader promotion in a category on a store’s overall profit will depend on the relative strengths of these two effects and can either be positive, negative or insignificant. Also, the intrinsic heterogeneity in consumer preferences implies that the nature and level of such net effect will vary across product categories. So, after gaining insights into the aggregate effects of loss leader promotion on store performance, the next question of interest to both store and category managers is the relative store profit impacts of loss leader promotions across different product categories. Given the limited advertising and promotion resources, the insights to this question becomes an important input to store managers’ decision to choose which categories to focus for loss leader promotions.

Various researchers (e.g., Chiang 1991; Gupta 1988; Van Heerde, Gupta and Wittink 2003; Van Heerde, Leeflang and Wittink 2004) have found that promotions have a considerable influence on switching of brands within a category with estimates ranging from 33 % to 94 %. Hence, it is natural to expect that promotions, especially loss leader promotions, should encourage consumers to visit the store and once inside the store, they will buy other non-promoted and high margin items. In this context, several studies have studied the role of category characteristics on the promotional response across different categories (e.g., Bell, Chiang and

Padmanabhan 1999; Fader and Lodish 1990; Mace and Neslin 2004; Nijs, Dekimpe, Steenkamp, and Hanssens 2001; Narasimhan, Neslin and Sen 1996). However, none of these studies has looked at the impact of loss leader promotions. Recently, Ailawadi, Harlem, Cesar and Trounce (2006), using data from CVS drug store, find that more than half of the individual promotions run by CVS are not profitable. At the same time, they also find that there is a large impact on the over-all sales of the store and a significant positive ‘halo effect’ of promotions (where for every unit of gross lift, 0.16 unit of some other product is purchased elsewhere in the store). While studying the impact of price promotions on manufacturers and retailers, Srinivasan et al (2004) also find a negative effect of price promotions on retailer margins. However, neither of these studies explicitly analyzes the impact of loss leader promotions. To the best of our knowledge, only two studies as noted below have investigated the category level impacts of loss leader promotions on store profit.

Using data from three stores, Walters and Rinne (1986) find certain portfolios of products promoted as loss leaders to have a greater impact on store traffic, store sales and deal sales than other product portfolios. However, they found that none of the portfolios of loss leaders had a significant impact on retailer profits. On the other hand, in another study using data from two stores, Walters and MacKinzie (1988) find that two (out of eight) of their categories had significant effects on store profits – one positive and one negative. However, as noted earlier, findings from both these studies suffer from the limitations of not controlling for the mediating role of feature promotions on store performance as well as for not including any competitive promotion effects. By explicitly controlling for the mediating role of feature promotions of both focal and competitive stores, our analysis will be able to provide more unbiased estimates as well as more generalizable results because of much larger sample size (24 stores).

Another limitation of the aforesaid two studies is that they did not consider a better measure of defining the loss leader promotions. A retailer typically has only a few items on loss leader promotions in a category promoted with varying discount levels. Entire category is never put on loss leader promotions. However, these studies relied just on a dummy variable method to define whether a category was on loss leader promotion, and thus were not able to represent the breadth of loss leader promotions within a category in constructing a measure of such promotions. We are able to avoid this limitation due to the richness of data available to us for this study.

As part of our analysis, we should note that we will also be able to obtain insights into the relative impact of feature promotion on store performance across different categories. Previous relevant research has found that feature promotions have a considerable effect on influencing brand choice decisions (Chintagunta et al, 1991) and sensitivity to feature promotions also varies with the demographic and competitive characteristics of the area (Ainslie and Rossi, 1998; Boatwright, Dhar and Rossi 2004 and Hoch, Kim, Montgomery and Rossi 1995). However, to the best of our knowledge, no research has shed light on the differential impacts of feature promotion of various categories on the performance of a store.

Table 1 provides an overview of the relevant existing studies and Table 2 summarizes our specific research questions both in terms of testing of conventional wisdoms and theoretical expectations as well as providing insights into essentially open empirical questions. “*Block 1*” represents the Aggregate-Aggregate level analysis research questions, and “*Block 2*” represents the Aggregate-Disaggregate level analysis research questions.

[Insert Tables 1 and 2 here]

EMPIRICAL ANALYSIS APPROACH

In this section, we discuss the specifications and structures of our empirical models used to address the specific research issues noted earlier. Figure 1 provides a stylized but useful conceptual overview of our empirical analyses. The dependent variables of interest in our analyses are the aggregate store performance measures in terms of traffic, sales and profits. The focal independent variable in our analyses is the extent of loss leader promotion activity, which is analyzed at both aggregate store as well as at disaggregate category levels. However, to avoid omitted variable bias we also need to control for the presence of non-loss leader promotions in our analysis.

Promotions can be described in terms of both breadth (percentage of items sold as loss leaders), the measure of promotions used by Richards (2007), and depth (the average percentage discount on these items (Ailawadi et al. 2006)). Specifically, the average depth of loss leader promotions can be expressed as $D_L = (1/n_L) \left(\sum_L (1 - p^S / p^R) \right)$, where n_L is the number of loss leader items, p^S is sale price, p^R is regular price. Similarly the average depth of non-loss leader promotions can be expressed as: $D_{NL} = (1/n_{NL}) \left(\sum_{NL} (1 - p^S / p^R) \right)$, where NL refers to non loss leader promotions². We define the breadth of loss leader promotions as $B_L = n_L / N$, where N is total number of items, so that breadth is the share of items on loss leader. Similarly, $B_{NL} = n_{NL} / N$, is the breadth of non-loss leader promotions. Then the average discount as a proportion of regular price on all N items is:

$$AD_N = B_L D_L + B_{NL} D_{NL} = AD_L + AD_{NL}, \quad (1.)$$

² A loss leader has $P^S < \text{both } P^R \text{ and } C^S$, where C^S is the unit cost of the item. A non loss leader promotion has $P^R > P^S > C^S$.

where AD_L is average discount due to loss leaders, AD_{NL} is average discount due to non loss leader promotions, and discount on the $N-n_L-n_{NL}$ non-promoted items is zero by definition. We propose $AD = \text{breadth} \times \text{depth}$ as a measure of opportunities to benefit from loss leader and non-loss leader promotions at both category and aggregate levels. This measure incorporates both the average size of discounts conveyed to consumers, and the proportion of items receiving the discounts. We will scale AD as a percentage, so that it can vary between 0 (no discount) and 100 (all items are free).

[Insert Figure 1 here]

Aggregate-Aggregate Model (Model 1)

We first describe the model specification at the aggregate level. Based on the conceptual framework of Lam et al (2001) for analyzing store performance, aggregate store profit, π , can be expressed as the product of average margin, m , sales per customer or average spending, \bar{S} , and traffic, T :

$$\pi = m\bar{S}T \quad (2.)$$

Assume that the manager wishes to determine the profit-maximizing discount due to loss leaders, AD_L . The first order condition is:

$$\frac{\partial \pi}{\partial AD_L} = \frac{\partial m}{\partial AD_L} \bar{S}T + \frac{\partial \bar{S}}{\partial AD_L} mT + \frac{\partial T}{\partial AD_L} m\bar{S} = 0 \quad (3.)$$

Dividing through by $m\bar{S}T$ and rearranging, we get:

$$-\frac{\partial \log m}{\partial AD_L} = \frac{\partial \log \bar{S}}{\partial AD_L} + \frac{\partial \log T}{\partial AD_L} \quad (4.)$$

If the optimal depth and breadth of loss leaders are to be set separately, similar expressions to Equation 4 can be developed for derivatives with respect to depth and breadth.³

Since an interior solution for the maximum L requires that the second derivative of Equation 3 be negative, and that there be diminishing returns to at least one component of profit, our empirical model must allow for this. Also, as feature and other variables are likely to interact with loss leaders (a loss leader on feature should generate more traffic than one that is not), we measure T and \bar{S} on a log scale to allow this interaction. Further, since there are likely to be diminishing returns to AD_L , we measure this variable on a log scale in the traffic and sales equations⁴. To allow for an interior solution for AD_L , we represent margin as a log-linear function of AD_L . Various control variables are included in the vector X . These are measures of feature promotions of focal and competitive store, promotional efforts on non loss leader promotions AD_{NL} , temperature, holiday and seasonal variables. Finally, since some traffic generated by loss leaders may return to the store in the future, and since some consumers may stockpile items bought on loss leaders, loss leaders may have an impact on future traffic, sales per transaction and margins. To allow for this possible carryover effects, we incorporate lagged values of dependent variables into the analysis. Thus our aggregate-aggregate empirical model (Model 1) can be expressed as:

$$\begin{aligned}
 \log T_t &= a_T + b_T \log(AD_{L_t} + 1) + c_T X_{T_t} + \lambda_T \log T_{t-1} + e_T, \\
 \log \bar{S}_t = \log(S/T) &= a_S + b_S \log(AD_{L_t} + 1) + c_S X_{S_t} + \lambda_S \log \bar{S}_{t-1} + e_S, \\
 \log m_t &= a_m + b_m AD_{L_t} + c_m X_{m_t} + \lambda_m \log m_{t-1} + e_m,
 \end{aligned} \tag{5.}$$

³ Properties of the model employed in empirical analyses are discussed in the Appendix.

⁴ Researchers commonly express an equation in log-linear form when the dependent variable involves sales or frequency counts (Greene 2000; Lam et al 2001). The log-linear formulation also seems to be appropriate for our joint model as the time-series plots of store traffic, and store sales and store profits in our empirical illustrations show that the variance of these variables increases as their overall levels increase.

where we add one to AD before taking logs to allow for zero values.⁵ We expect b_T and b_S to be positive because loss leaders should increase traffic and sales. Conversely, we expect b_m to be negative because loss leaders should adversely affect margins (see Appendix). Equation 4 leads to a particularly tractable solution for the optimal value of L . Given Equation 5,

$\partial \log T / \partial AD_L = b_T / (AD_L + 1)$, $\partial \log S / \partial L = b_S / (AD_L + 1)$, $\partial \log m / \partial AD_L = b_m$. Substituting into Equation 4, and solving for AD_L gives the following expression for the profit-maximizing value of AD_L :

$$AD_L^* = -\frac{b_T + b_S}{b_m} - 1. \quad (6.)$$

For an interior solution, the optimal value of AD_L^* must lie between 0 and 100. It can be shown that the second-order condition for maximum AD_L^* is satisfied if profit at the optimal AD_L^* is positive and if $b_T + b_S$ is greater than zero.

Aggregate-Disaggregate Model (Model 2)

For this analysis, we have the aggregate or store level measures as dependent variables and we have the category or disaggregate level measures of loss leader and feature promotions as the independent variables. A retailer typically has only a few items on loss leader promotions in a category. While past research (Walters and MacKenzie 1988; Walters and Rinne 1986) represents the loss leader promotion as a binary variable representing whether there is a loss leader promotion in the category, the impact of the promotion is likely to be affected by its breadth and depth. For example, a broader promotion in a category may attract different consumers into the store who have different brand/size preferences. A deeper promotion in a

⁵ Because the estimated values of the lagged coefficients may capture omitted variables as well as carry over effects, we focus on short-run optimization in our empirical analysis. If the lagged dependent variables do accurately measure carry over effects, long-run effects are given by the short-run values divided by the corresponding values of $(1-\lambda)$. See, for example, Greene (2000), p. 722.

category increases the potential discount on a consumer's market basket, making a visit to the store more attractive. To account for both the breadth and depth dimensions of category promotions, we employ average discounts due to loss leaders AD_{Lc} , as our category-specific measure of loss leaders.

Since loss leaders cannot attract traffic without being known prior to the store visit, we interact AD_{Lc} with a dummy variable representing presence of a feature promotion in that category in the traffic equation. Otherwise the model specification is the same as Model 1. Thus the aggregate-disaggregate empirical model (Model 2) may be expressed algebraically as:

$$\begin{aligned}\log T_t &= a_T + \sum_c b_{Tc} (F_c \log(AD_{Lc_t} + 1)) + \gamma_T X_{Tt} + \lambda_T \log T_{t-1} + e_T, \\ \log \bar{S}_t = \log(S/T) &= a_S + \sum_c b_{Sc} (\log(AD_{Lc_t} + 1)) + \gamma_S X_{St} + \lambda_S \log \bar{S}_{t-1} + e_S, \\ \log m_t &= a_m + \sum_c b_{mc} (AD_{Lc_t}) + \gamma_m X_{mt} + \lambda_m \log m_{t-1} + e_m,\end{aligned}\tag{7.}$$

where the subscript c refers to the product category, and we add one to AD_{Lc} before taking the log to allow for AD_{Lc} to have zero values. In Equation 7 effects of non-loss leaders and other demand shifters are included in the vector of control variables, X .

Expressions for the optimal breadth of loss leaders for each category that are analogous to Equations 3,4 and 6 can be obtained as follows. For choice of optimal AD in each category

conditional on offering a feature, the analog of Equation 4 is: $-\frac{\partial \log m_c}{\partial AD_{Lc}} = \frac{\partial \log \bar{S}_c}{\partial AD_{Lc}} + \frac{\partial \log T_c}{\partial AD_{Lc}}$.

Differentiating Equation 6 with respect to each AD_{Lc} , setting the results to zero, and solving, gives the optimal interior values of AD for each category conditional on whether a feature is

offered:

$$AD_{Lc}^* = -\frac{b_{Tc} F_c + b_{Sc}}{b_{mc}} - 1\tag{8.}$$

for any category c . For an interior solution, the optimal value of AD_{Lc}^* must lie between 0 and 100. Second order conditions for a maximum require $b_{Tc}F_c + b_{Sc} > 0$, which implies in turn that b_{mc} must be negative for an interior solution.

Feature activity is presented as a given in the above analysis. Feature decisions can be made for any category c by comparing the ratio of profit with a feature (π_{Fc}) and profit without (π_{0c}). It is easily shown that π_{Fc}/π_{0c} cannot exceed one unless b_{Tc} is positive, e.g., unless the loss leader generates an increase in traffic. In general it would be optimal in our framework for the retailer to rank categories in order of π_{Fc}/π_{0c} , and to allocate features in order of the ranking until the available space for features is used up.

DATA DESCRIPTION

The data for our study comes from a suburban area grocery market of a mid-size city in the Northeastern U.S. The market is effectively a duopoly market with two regional competing retail grocery chains accounting for more than 85% of the market share. For this study, we are able to get cooperation from the management of one chain, which provided us access to data on transactions of the customers at its stores throughout the study period. We are also given access to recent historical transaction and profit contribution data of its customers. The data constitutes 24 stores of the chain. The duration of the data is 55 weeks (May 2004 to June 2005).

We supplement the purchase data with the store flyer data of both focal and competitor stores. Store flyers contain items that are on feature promotion in stores. The items featured on the cover page are classified in the categories chosen by manually going through all the items. We did not have data on display activity, or on prices at the competing chain. Since it is unlikely that there was an appreciable change in the regular prices of the focal store relative to the competitor during the period of the study, we did not attempt to construct an overall index of

regular prices. Our assumption is that the major competitive price effects occur through promotions. This is consistent with Ailawadi et al. (2006), who focused on promotions as the key determinant of sales relative to a baseline.

We also supplement the data with the information on temperature and the dates of certain holidays. For temperature information, we first obtained historical (hour by hour) temperature data from the National Oceanic and Atmospheric Administration of the city where the stores are located⁶. From these data, we calculated a mean temperature for each week of the duration of the data. Because there are often large increases in demand at holiday periods, it is important to account for holiday effects. We considered the following holidays: New Year, Super Bowl, Valentine's Day, Easter, Memorial, Independence Day, Labor Day, Halloween, Thanksgiving and Christmas. Since, the weekly promotions end on Saturdays, if any of these holidays fell on a Monday, we considered the week before also as the holiday week while creating the dummy variable for the holiday (Chevalier et al 2003). Finally, we also considered the seasonal effects for fall, winter, spring and summer seasons.

The retailer maintains a detailed record of the financial information for each UPC including the wholesale price; various types of costs including warehousing, stocking, wages of employees etc., any manufacturer funding of promotions, and quantity discounts obtained by the retailer. Using the cost information from various activities, the retailer computes an average cost of each UPC for each week. Consistent with Gauri, Sudhir and Talukdar (2008), this average cost was used as the criterion for classifying items as loss leaders. Thus our operational definition of a loss leader on a given week is that the price of an item is below the retailer's average cost for that week. Since the discounts on items identified as loss leaders are generally

⁶ These data can be found at www.noaa.gov.

much deeper than for other promotions, our demand models should accurately portray consumer response to deep discounts even if there are some errors in classifying items as loss leaders.

For the store level analysis, data from the entire store was used to get the required measures. Table 3 summarizes the aggregate-level data on dependent variables, promotional variables and temperature, an independent variable that may influence traffic and sales. An average store has 13836 transactions per week with an average volume per transaction of \$15.39. The gross margin of an average store is around \$0.23 per dollar sold. The focal store appears to feature about twice as many different categories than its major competitor. About 11 percent of the store's items are estimated to be on loss leader in an average week, and the average discount on these loss leaders is about 29 percent. The percentage of non-loss leader items on promotion is higher, around 33 percent, but the average depth of discount on these items is only about 9 percent. In sum, the store offers a relatively smaller proportion of deeply discounted items, and a much larger proportion of items with more shallow discounts.

[Insert Table 3 here]

For the category level analysis, aggregate sales, traffic and margin were still used as dependent measures. However, to construct independent measures, we partitioned the store into 27 categories. Given the large number of UPCs in each of the 27 categories, we had to simplify our analysis to make it tractable. Accordingly we limited our analysis to the best selling UPCs in each category, where the number of UPCs was selected to account for at least 60 percent of category volume (Besanko, Dube and Gupta 2005; Singh, Hansen and Blattberg 2006). These better selling UPCs account for the vast majority of promotional activity.

Category level descriptive statistics for the data are shown in Table 4. Most categories have at least one item on loss leader in a given store in a given week; the notable exception is

eggs. Fewer categories receive feature promotion. The categories most commonly featured are meat, produce, refrigerated juices, paper products, carbonated soft drinks, ice-cream, prepared foods, cereal, beer and laundry detergent. Features in these categories tend to be accompanied by loss leaders. Milk, oral care, pasta, salad dressing, coffee and tea and beauty care have at least one loss leader with no accompanying feature in over 75 percent of the store-weeks. When there is a loss leader in the category, soft drinks, milk and laundry detergent tend to have a relatively high share of the category on loss leader. When offered as loss leaders, items in the ice cream, prepared foods, snack food, and meat have the highest average discount on regular price. Combining breadth and depth, carbonated soft drinks, milk and ice cream have the highest average values of *AD*.

[Insert Table 4 here]

ANALYSIS OF THE EMPIRICAL MODELS

Econometric Issues

The major econometric issues faced by our analysis are permissibility of pooling across stores, the possibility of serial correlation in error terms, endogeneity of decisions to offer loss leaders, and possible bias from omitted variables. Preliminary tests of the homogeneity of coefficients across stores (but allowing for separate store intercepts) using the procedure due to Chow (1960) indicated that pooling is justified. For the 6 equations listed in Equations 5 and 7, F-ratios were less than one in 5 of these cases, and the null hypothesis of equal slopes across could not be rejected at the .01 level in the 6th case. Similarly, tests on the pooled data did not reveal significant serial correlation.

Since *AD*, and its components - breadth and depth - are managerial decision variables, the possibility that they are endogenous must be taken into account. We account for the possible endogeneity of these decision variables by incorporating instruments for these variables in both

the aggregate and category-level analyses, and using 2-stage least squares in which the various measures of discounts due to both loss leader and non loss leader promotions are treated as endogenous. Since serial correlation does not appear to be significant, we employ lagged values of measures of discounts, and lagged values of traffic, sales per transaction and margin as instruments (Chintagunta 2001; Sudhir 2001). We also employed lagged values of the exogenous variables as well as the current values as instruments. While feature activity may also be endogenous to some extent, we treated this as exogenous because it was not our primary focus. This is consistent with other prior research (e.g., Chintagunta 2001).

Since there was no evidence of systematic changes in the relative non-promoted prices of the items sold in the competing stores, and since feature and promotion activity are viewed as the main driver of switching between stores, we do not include a measure of regular prices in our analysis. Another reason for this is the practical difficulty of constructing overall indexes of regular price for the competing stores that will accurately capture market basket prices for their consumers, especially given lack of ready access to price data at the competing store. We do control for all promoted prices of the focal store by computing the discount measures described above for both loss leader and non loss leader items. As noted above, we also control for feature activity at the focal and competing chain, holidays, stores, and temperature.

A remaining issue is possible omitted variables bias due to lack of complete data on competitive loss leaders, and other competitive promotions. However, we were able to control for competitive feature activity, which should constitute the major source of information for consumers who are drawn to the competitor's stores due to promotions. This should mitigate any omitted variable problems due to lack of competitive data.

Results for Model 1

The results for the aggregate-aggregate level model (Model 1), which was estimated on data pooled across stores with store fixed effects included, are shown in Table 5. The results in the top panel use the *AD* measures as independent variables, while the bottom panel results break *AD* for loss leaders into their breadth and depth components. The results in the top panel indicate that *AD* for both loss leaders and non loss leaders affects traffic. However the effect, which can be interpreted as elasticity, is slightly larger for the loss leaders. The main impact of loss leaders is on traffic rather than sales per transaction. As one would expect, loss leaders also appear to significantly decrease margins. The results in the bottom panel indicate that when loss leader activity is broken into its breadth and depth, breadth is significantly related to traffic, while depth is significantly related to sales per customer. Thus it appears that offering a variety of loss leaders is most likely to induce shoppers to come to the store, while deep discounts lead to higher sales per customer and higher margins. This result may indicate that the deep discounts are more successful at attracting large basket customers who also buy items that are not discounted.

[Insert Table 5 here]

Since the feature variable in Table 5 is the percentage of categories featured, and since the total number of items featured does not vary much from week to week, the feature variable is primarily capturing the variety of items featured. The negative sign on this variable in the traffic equation suggests that a high percentage of categories featured is less effective than a smaller percentage. This may be because the high percentage includes categories that are less able to attract traffic. Conversely the results on breadth of loss leaders presented above suggest that a higher proportion of items on loss leader in more popular categories – high breadth – may enhance traffic. The positive sign on percentage of items featured in the sales equation suggests

that a higher percentage of categories featured may be more effective at generating sales per customer because a larger proportion of the buyer's assortment is on feature. For a similar reason, a large proportion of categories featured by the competitor may have been successful at attracting large basket customers away from the focal store. Lagged traffic and margin have significant positive effects, suggesting a positive carry-over of traffic and margin. Conversely, lagged sales had a significant negative effect, suggesting stockpiling behavior.

Results for Model 2

Since there are 27 categories, estimation of Model 2 posed a challenge. Because the competitor and focal chain varied the categories in which they promoted over time, factor analyses indicated that there was no gain to reducing the number of categories by working with combinations of promotions as done by Walters and Rinne (1986). Still, while the mix of promotions showed varying patterns over time, the large number of parameters required for estimating the effects of competitive feature and the *AD* measures for both loss leaders and non-loss leaders for each category created collinearity problems.

Our solution was to impose constraints on the coefficient estimates that are consistent with our knowledge of how the promotions should work. Specifically, since it is unlikely that consumers would decide *not* to shop at a store because an item was featured, we constrained the effects of the interactions of feature**AD* to be non-negative in the traffic equation. Assuming that the primary effect of feature is to drive traffic, and that price effects take precedence once the consumer is at the store, we include *AD* in the sales equation, and not the feature**AD* interaction. Because price reductions should lead to increased revenue, we constrained the coefficient of *AD* to be nonnegative in the sales equation.⁷ Similarly, because it is unlikely that a feature at the

⁷ Promotions could decrease revenue per customer if they brought in a large enough proportion of cherry pickers. However, existing literature indicates that this is unlikely (Fox and Hoch 2005; Gauri, Sudhir and Talukdar 2008).

competitor store would motivate consumers to shop at the focal store, we constrained the effects of the competitor feature dummy variables to be non-positive in the traffic and sales equations. Finally, we eliminated categories that did not demonstrate a positive effect on either traffic or sales from the margin equation, and constrained the coefficients of the remaining categories in this equation to be negative, consistent with the expectations outlined above.

Model 2 was estimated using nonlinear two stage least squares (using *proc* model in SAS) in which the various effects of the AD variables were treated as endogenous as described above, and the constraints outlined above were imposed on the models. Independent variables for AD_L and AD_{NL} were included in the traffic equation for all 25 of the 27 categories (eggs and milk were never featured), and independent variables for AD_L and AD_{NL} were included in the sales equation for 26 of the 27 categories (eggs were never promoted). As explained above, independent variables for AD_L and AD_{NL} were included in the margin equation only if their coefficients were positive in either or both of the traffic and sales equations.

Results for Model 2 are presented in Table 6. To conserve space, categories that did not have a positive effect in either the traffic or sales equation are excluded from the table. The results in Table 6 indicate that the interactions of loss leader and feature are positively related to traffic in 12 of the 25 categories in which this interaction is observed, with the results being significant at .05 for 8 of the categories: meat, produce, prepared foods, cereal, cheese, condiments, coffee and tea, and fresh seafood. We were unable to detect significant traffic effects for four of the most heavily featured categories: refrigerated juices, paper goods, carbonated soft drinks and ice cream. Since these categories had the smallest coefficients of variation in the feature*AD interaction, a likely reason for this is lack of variation in this

variable. That is, since there are almost always features that have similar discount levels in these categories, it is hard to identify traffic effects for these categories.

The results in Table 6 indicate positive effects of loss leaders on sales per transaction for 10 categories, with the results being significant at .05 for 6 categories – produce, ice cream, prepared foods, cheese, beauty care and pasta. The positive effects of loss leaders on sales and traffic effects are offset by negative margin effects for 11 categories. We will calculate the net effects of loss leaders on profits that implied by these estimates in the next section.

The results in Table 6 also indicate positive traffic and sales effects of non loss leader promotions, most notably significant effects of beer, spreads and oral care on traffic, and significant effects of carbonated soft drinks, frozen or canned fruits and vegetables, bakery products and snack food on sales per transaction. Finally, competitive features in a number of categories are significantly related to reduced traffic and sales per transaction.

[Insert Table 6 here]

Profitability Analysis

To gain insight into the profitability of loss leaders, we compare the estimated profits given the actual and optimal levels of loss leaders with the estimated profits if loss leaders are eliminated and everything else remains the same. If loss leaders are eliminated, $AD = 0$ and $\log(AD + 1) = 0$. Thus, if the subscript a denotes actual and the subscript o denotes absence of loss leaders, it follows from Equation 5 that:

$$\begin{aligned}\log T_a - \log T_o &= b_T \log(AD_{L_a} + 1) \\ \log \bar{S}_a - \log \bar{S}_o &= b_S \log(AD_{L_a} + 1) \\ \log m_a - \log m_o &= b_m AD_{L_a}\end{aligned}$$

It follows that:

$$\begin{aligned} \log \pi_a - \log \pi_o &= (\log T_a - \log T_o) + (\log \bar{S}_a - \log \bar{S}_o) + (\log m_a - \log m_o) \\ &= (b_T \log(AD_{L_a} + 1)) + (b_S \log(AD_{L_a} + 1)) + (b_m AD_{L_a}) \end{aligned} \quad (9.)$$

and that $\pi_a/\pi_o = \exp(\log \pi_a - \log \pi_o)$. A similar expression can be derived for the ratio of profits with optimal loss leaders relative to no loss leaders if estimated optimal values of AD are derived as in Equation 8 are substituted for the actual ones. Expressions for individual categories can also be derived in the same manner as Equation 8 from the expressions in Equation 7.

The results of this profitability analysis are presented in Table 7. The top panel compares profits between the actual average value of AD and profits if all loss leaders are eliminated. For Model 1 the table indicates that positive traffic and sales effects are offset by negative margin effects so that the overall profitability of loss leaders is estimated to be only 0.7 percent above profit without loss leaders. The t-test on the sum of the logs of the effects indicates that this difference is not significantly above zero.⁸ In the bottom panel, the results for Model 1 indicate that profits could be improved by reducing AD by roughly 60 percent (1.317/3.237).

[Insert Table 7 here]

Based on Model 2, we were able to calculate actual profits relative to profits with no loss leaders for 15 categories; other categories did not show positive effects of traffic or sales. Based on the results in Table 7, ice-cream, prepared foods, cereal, frozen or canned fruits or vegetables and cheese are significantly more profitable with loss leaders than without, while beer and beauty care appear to be significantly less profitable. Multiplying the ratios of profits with loss leaders to profits without across the 15 categories gives 1.098, which is an estimate of the overall ratio of profits with loss leaders to profits without if this ratio is one for all other categories. Thus Models 1 and 2 indicate that profits increase between 0.7 and 9.8 percent due to loss leaders.

⁸ The standard deviation of the sum is the square root of AD^2 times the sum of the variances of the coefficients of AD for traffic, sales and margin.

The results in the bottom panel of Table 7 provide calculations of the estimated optimal AD for categories exhibiting negative margin effects; this calculation cannot be done for categories in the top panel that did not have a negative coefficient on margin. Comparing optimal to actual values, the results indicate that AD should be increased for ice cream, condiments and coffee and tea, kept about the same for fresh seafood, and decreased for other categories. They also indicate that an optimal allocation of loss leader promotion efforts across categories will generate an *additional* 3.2 to 7.5 percent in overall store profit compared to that generated from the current loss leader promotion efforts. The relatively small difference between optimal and actual store profit levels indicate that the profit functions faced by grocery retailers tend to be flat, which is consistent with the typically thin profit margin in the grocery retail industry. At the same time, it is important to recognize that the grocery retail industry is also characterized by high sales volume. For instance, according to *Food Marketing Institute*, the average monthly sales volume per supermarket store in 2007 was about \$1.5 million⁹. So, any promotional strategy that boosts store profit even by a relatively small percentage amount can potentially produce a significant increase in terms of total dollar profit for a grocery retailer.

In general, our results indicate that the focal chain's loss leaders do increase traffic and sales per transaction. But these increases come at the expense of significant reductions in margin, limiting their profitability. These results are similar to those of Ailawadi et al. (2006) who found that promotions at CVS generate substantial incremental lift and incremental sales for other categories, but are often unprofitable because of negative effects on margin.

SUMMARY INSIGHTS AND CONCLUSION

Loss leader promotion strategy is one of the most prevalent price promotion strategies used by the grocery supermarket retailers. It is distinct from other retailer price promotion

⁹ Source: *Food Marketing Institute* Web site www.fmi.org (Accessed September 12, 2008)

strategies as the price of the loss leader product is set at or below retailer's marginal cost.

Conventional wisdom and theoretical expectations are that the negative contribution from the loss-leader items bought by the customers will be more than offset by the profit generated from the sale of non-loss-leader items to them. Unfortunately, despite the fact that the loss leader promotion strategy is widely prevalent in practice in the grocery retail market, there have been very few systematic empirical studies in terms of its effectiveness on the performance of the retailers. Even these few empirical studies base their findings on small sample sizes and without controlling for the important mediating role of feature promotions of neither focal nor competing stores. As such, while conventional wisdom and theoretical studies posit a potential positive role of loss leader promotion strategy on retailer performance, many critical aspects of such role – especially on retailers' profit performance – remain essentially open empirical questions. In this study, we present what we believe to be several key, hitherto unavailable empirical insights into the impact of supermarket retailers' loss leader promotion strategy on their store performance measures. They also provide several interesting and important strategic implications for retailers.

The aggregate level analyses show that the “breadth” of store-wide loss leader promotion is most likely to induce increased store traffic, while its “depth” leads to higher sales per customer and higher margins. This result may indicate that the deep discounts are more successful at attracting large basket customers who also buy items that are not discounted. We find that store profits increase between 0.7 and 9.8 percent due to loss leaders. The disaggregate level analyses show marked differences across product categories in their relative effectiveness as loss leaders in boosting store profit. We show how our results can be used by retailers to further improve overall store profits through loss leader promotions by reallocating promotion efforts across different categories. We find that such reallocation of loss leader promotion efforts

across categories can increase store profit by an additional 3.2 to 7.5 percent that reflects a potentially significant boost to total dollar profit in the low margin-high volume business context of grocery retailers.

Our results suggest that aggregate results, though very important in studying the overall performance of the retailer, should be used in conjunction with the disaggregate results to get deeper insights. When both disaggregate and aggregate results are considered together, then only the retailer can get a complete picture of whether such a strategy should be used or not. It is also very important to consider the mediating role of feature promotions of both focal store as well as the competitor store. Finally, a finding which has great implications is that it is necessary to take into account the control variables (competitive feature activity, temperature, season, and holidays) as they explain a significant proportion of the variation in the performance measures.

We hope that our findings and the substantive issues they highlight will stimulate further research in the area of loss leader promotion, which has received limited attention so far. While our study presents an important step towards an integrated, systematic analysis of the impact of loss leader promotions on store performances, it is subject to several limitations that lend themselves to several interesting future research directions. First, analysis should also be done at brand and potentially at UPC level to study the effect of loss leader promotions with or without feature promotions on the performance of the brands/SKUs being promoted. Some of the frequently promoted and strong brands may have a greater impact and may be influencing other brands/SKUs in an asymmetric manner. Second, sometimes manufacturers whose brands appear in the flyer pay certain promotional fees to the retailer as an incentive. Since we do not have detailed information about such trade deals, hence we are not able to identify such deals and separate their impact on store performance. Third, mediating role of displays and other in-store

special promotion activities like end of aisle, etc should be taken into consideration while considering the sale of all, especially loss leader items. Finally, other detailed measures of competitive promotions like their price indices in similar categories and in-store promotions should be taken into consideration in future work studying the competitive impact of loss leader promotions.

APPENDIX MODEL DERIVATIONS

We will derive results for a model with c product categories. Aggregate store profit, π , can be expressed as the product of average margin, m , sales per customer or average spending, \bar{S} , and traffic, T :

$$\pi = m\bar{S}T = \sum_c (p_c - w_c) * Q_c$$

(A1.)

where p is retail price, w is unit cost and Q is units sold (we suppress a subscript for time for simplicity). The first-order condition for the profit-maximizing discount due to loss leaders, AD_{Li} for any category i can be expressed in two equivalent ways:

$$\frac{\partial \pi}{\partial AD_{Li}} = \frac{\partial m}{\partial AD_{Li}} \bar{S}T + \frac{\partial \bar{S}}{\partial AD_{Li}} mT + \frac{\partial T}{\partial AD_{Li}} m\bar{S} = 0 \quad \text{or} \quad (A2.)$$

$$\frac{\partial \pi}{\partial AD_{Li}} = Q_i \frac{\partial p_i}{\partial AD_{Li}} + \sum_c (p_c - w_c) \frac{\partial Q_c}{\partial AD_{Li}} = 0 \quad (A3.)$$

where the first term in A3 is negative and represents the loss on original units due to the price reduction, while the second term represents the gain due to increased quantity. Dividing

Equation A2 through by $m\bar{S}T$ and rearranging we get $\frac{\partial \log \bar{S}}{\partial AD_{Li}} + \frac{\partial \log T}{\partial AD_{Li}} + \frac{\partial \log m}{\partial AD_{Li}} = 0$.

The model in Equation 7 is repeated below in a simplified form, in which we ignore the impact of feature advertising and other variables to simplify notation:

$$\begin{aligned} \log T &= a_T + \sum_c b_{cT} (\log(AD_{Lc} + 1)) + e_T \\ \log \bar{S} &= a_S + \sum_c b_{cS} (\log(AD_{Lc} + 1)) + e_S \\ \log m &= a_m + \sum_c b_{cm} (AD_{Lc}) + e_m \end{aligned} \quad (A4.)$$

Since $\bar{S}T$ and $\sum_c p_c Q_c$ are equivalent expressions for total revenue, we can write:

$$\frac{\partial \bar{S}T}{\partial AD_{Li}} = (b_{iT} + b_{iS}) \frac{\bar{S}T}{(AD_{Li} + 1)} = Q_i \frac{\partial p_i}{\partial AD_{Li}} + \sum_c p_c \frac{\partial Q_c}{\partial AD_{Lc}}. \text{ These provide equivalent expressions}$$

for marginal revenue. In our empirical model, marginal revenue will decrease with AD_{Li} if

$(b_{iT} + b_{iS})$ lies between 0 and 1.

Now consider the margin, m . Equation A1 implies that $\log m = \log \pi - \log \bar{S}T$.

Differentiating with respect to AD_{Li} gives:

$$\frac{\partial \log m}{\partial AD_{Li}} = \frac{\partial \log \pi}{\partial AD_{Li}} - \frac{\partial \log \bar{S}T}{\partial AD_{Li}} = -\frac{1}{\sum_c p_c Q_c} \left(Q_i \frac{\partial p_i}{\partial AD_{Li}} + \sum_c p_c \frac{\partial Q_c}{\partial AD_{Lc}} \right) \quad (\text{A5.})$$

since $\frac{\partial \log \pi}{\partial AD_{Li}} = 0$ if the seller is maximizing profits. From the condition that marginal revenue

equal marginal cost in Equation A3, $Q_i \frac{\partial p_i}{\partial AD_{Li}} + \sum_c p_c \frac{\partial Q_c}{\partial AD_{Lc}} = \sum_c w_c \frac{\partial Q_c}{\partial AD_{Lc}}$. This implies that

$$\frac{\partial \log m}{\partial AD_{Li}} = -\frac{1}{\sum_c p_c Q_c} \left(\sum_c p_w \frac{\partial Q_c}{\partial AD_{Lc}} \right), \text{ which is negative. That implies that coefficients } b_{cm} \text{ in the}$$

expression for m in Equation A4 should be negative. Intuitively loss leaders increase volume at a decreasing rate, while they lead margins to decline until a point is reached where the marginal revenue from additional discounts equals the marginal cost of increasing the volume.

Equivalently marginal revenue declines because the tradeoff between additional volume and increased losses due to the discounts becomes less favorable, and eventually equals the marginal cost of the additional volume. This declining marginal revenue creates the lower margins.

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FIGURE 1 : CONCEPTUAL FRAMEWORK

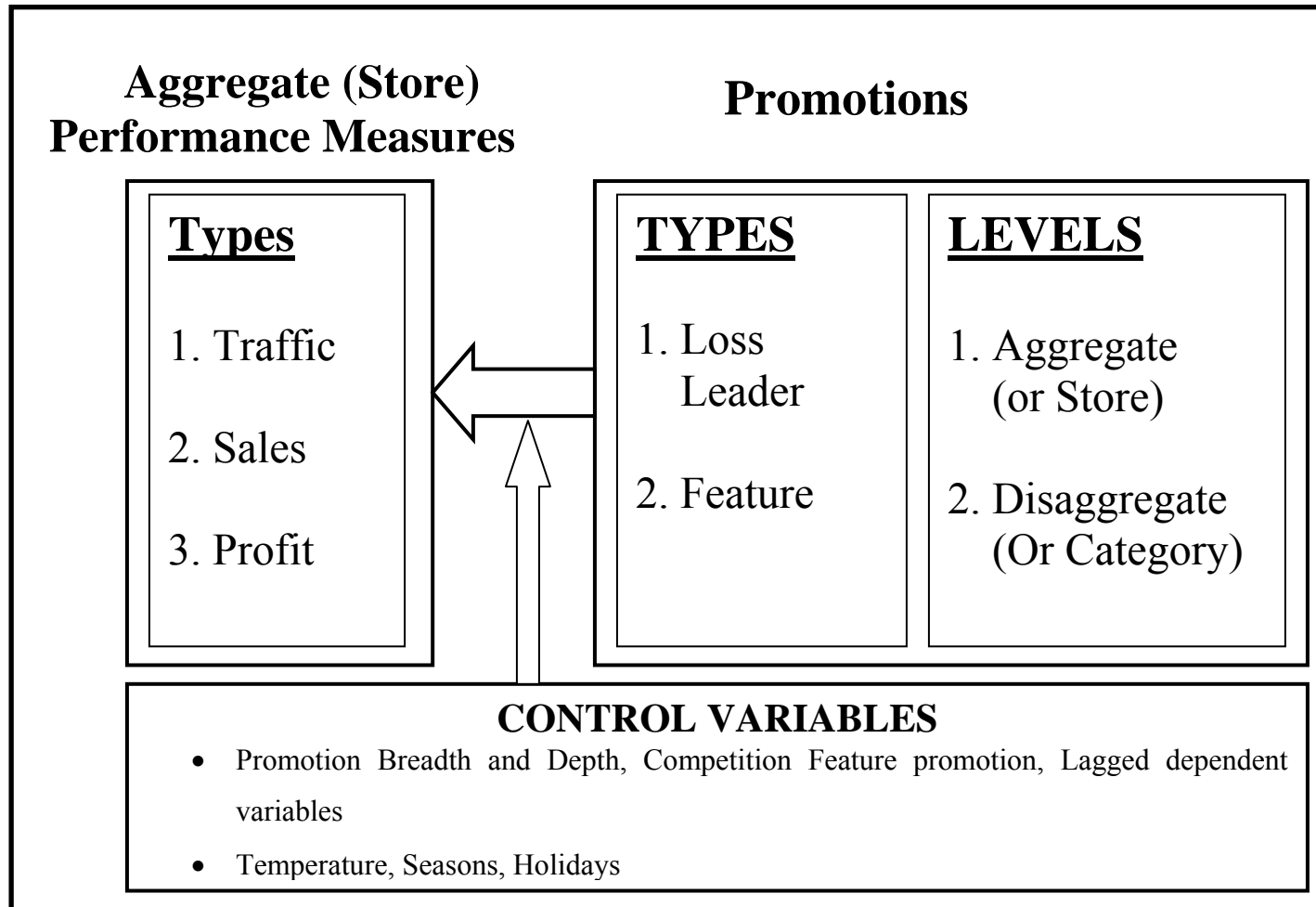


TABLE 1: RELEVANT EMPIRICAL STUDIES

<i>Reference</i>	<i>Dependent Variable (s)</i>	<i>Sample Size</i>	<i>Explanatory Variables</i>	<i>Level of Data Analysis</i>	<i>Number of Categories Considered</i>	<i>Comments</i>
Walters & Rinne, 1986	Store Sales, Profit, traffic	3 Stores	Promotion variables - double couponing, loss leader portfolios and holidays	Aggregate	10 Loss leader product portfolios	Certain portfolios of loss leader items affected store traffic and sales. No significant effect on profits.
Walters & MacKenzie, 1988	Store Sales, Profit, traffic	2 stores	Promotion variables - loss leader dummy, in store specials and holidays	Aggregate	8 different Loss leader	Certain loss leader categories affected store traffic and sales. No significant effect on profits.
Mulhern & Leone, 1990	Store Sales, Traffic	1 Chain, 104 weeks	One time change in featuring strategy (many shallow to few deep discounts)	Aggregate	-	Change in promotion strategy of the store from featuring many items at small discount to a few items at deep discount lead to an increase in chain level sales but did not affect traffic
Mulhern and Padgett, 1995	-	11 stores (home improvement), 412 surveys	-	Individual	Promotion and non promotion items	Individual level regular price purchases are highly correlated with promotional price purchases. Among shoppers who identify promotions as one of the reasons for visiting the stores, about three quarter of them make regular purchases also.
Lam, Vandenbosch, Hulland, and Pearce, 2001	Front traffic, store-entry ratio, closing ratio and average spending	2 Chains (1 store of Apparel and 22 stores of Sporting good Chain)	Day of week, Christmas days, length of operation, external events and seasonality	Aggregate	Clothing and Sporting goods	Break down store sales in four components: front traffic, store-entry ratio, closing ratio and average spending. They find that price promotions have a positive impact on store entry and on the likelihood that a consumer will make a purchase
Gijsbrechts, Campo, Goossens, 2003	Store Sales, Traffic	55 stores, 52 weeks	5 Store Flyer and 7 Location Characteristics	Aggregate	-	Store traffic and sales are affected by flyer composition characteristics, such as the average discount, the share of in-flyer space allocated to food and private label items, the type of category featured on the cover page (specialties vs. produce, fish/meat), and, to a lesser extent by flyer size
Ailawadi, Harlem, Caser and Trounce, 2006	Store Sales, Profit	3803 stores of CVS, 52 weeks	Promotion, demographic and Competitive Characteristics	Aggregate	Health, Beauty, Edibles, Gen Merchandise, Photo Processing	More than half of the promotions run by CVS are not profitable, but there is large impact on the over-all sales of the store (about 16 % incremental lift, which they call as 'halo effect')
This Study	Store Sales, Traffic and Profit	24 Stores, 55 Weeks	Promotion, demographic and Competitive Characteristics	Aggregate and Disaggregate	All categories	Loss Leader Promotions have a differential impact on store performance but overall they are profitable for the store.

TABLE 2 : SUMMARY OF RESEARCH ISSUES

		Store Performance			
Pricing Strategy		<i>Traffic</i>	<i>Average Sales</i>	<i>Profit Margin</i>	<i>Overall Profit</i>
Store (or aggregate) level	Loss Leader	+	+	-	+
	Feature Focal	+	+	-	← Block 1
	Feature Competitor	-	-	-	
Category (or disaggregate) level	Loss Leader	+	+	-	+
	Feature Focal	+	+	-	
	Feature Competitor	-	-	-	← Block 2

TABLE 3: DESCRIPTIVE STATISTICS

Variable	Definition	Mean
<i>Traffic</i>	Number of unique transactions in a store in a week	13836
<i>Sales per transaction = Sales/Traffic</i>	Weekly sales in a store/traffic	\$15.39
<i>Margin = Profit/Sales</i>	Weekly profit in a store/weekly sales in a store	0.2328
<i>Pct Categories Featured</i>	(Number of categories featured/total number of categories)*100	47.41
<i>Pct Competitor Categories Featured</i>	(Number of competitor categories featured/total number of competitor categories)*100	23.64
<i>Breadth = Pct Loss Leaders</i>	(Number of Loss Leader UPCs in a week in a store/total number of distinct UPCs sold in the store in that week)*100	11.0341
<i>Depth of Loss Leaders</i>	Average over all LL items in a week in a store of ((Reg Price - Price in that Week)/Regular Price)*100	29.0429
<i>Breadth = Pct Non Loss Leaders</i>	(Number of Non Loss Leader UPCs in a week on price cut in a store/total number of distinct UPCs sold in the store in that week)*100	33.4712
<i>Depth of Non Loss Leaders</i>	Average over all Non LL items on price cut in a week in a store of ((Reg Price - Price in that Week)/Regular Price)*100	8.9593
<i>Average Discount for Loss Leaders (AD LL)</i>	Breadth*Depth of loss leaders	3.2366
<i>Average Discount for Non Loss Leaders (AD NL)</i>	Breadth* Depth of non loss leaders	2.8850
<i>Temperature</i>	Average temperature in a week in degrees Fahrenheit	53.51

TABLE 4: CATEGORY DESCRIPTIVE STATISTICS

Category	Proportion of Store Weeks						Average Proportion of Loss Leaders (Breadth)	Average Discount on Loss leaders (Depth)	AD LL %= Breadth*Depth* 100
	Avg. Pct. Of Volume from Category	At Least One Loss Leader in Store-week	Feature in Category	Feature and Loss Leader	Feature Only	Loss Leader Only			
Meat	19.29%	0.876	1.000	0.876	0.124	0.000	0.019	0.352	0.817
Produce	12.00%	0.536	1.000	0.536	0.464	0.000	0.018	0.232	0.814
Ice Cream	2.66%	1.000	0.873	0.873	0.000	0.127	0.206	0.469	9.657
Carbonated soft drinks	4.77%	1.000	0.891	0.891	0.000	0.109	0.535	0.331	17.646
Beer	2.60%	0.958	0.709	0.689	0.020	0.268	0.140	0.168	2.493
Prepared Foods	4.62%	1.000	0.764	0.764	0.000	0.236	0.125	0.362	4.518
Cereal	2.88%	1.000	0.745	0.745	0.000	0.255	0.176	0.187	3.105
Frozen or Canned Fruits/Veggies	2.92%	0.915	0.236	0.221	0.015	0.694	0.041	0.266	1.246
Cheese	4.33%	0.770	0.364	0.342	0.021	0.428	0.025	0.332	1.047
Bakery products	8.19%	1.000	0.400	0.400	0.000	0.600	0.064	0.320	2.072
Soup	1.35%	0.841	0.164	0.164	0.000	0.677	0.076	0.254	2.346
Milk	4.18%	0.977	0.000	0.000	0.000	0.977	0.382	0.318	12.107
Beauty Care	1.81%	0.998	0.200	0.200	0.000	0.798	0.105	0.243	2.608
Spreads	2.24%	0.664	0.309	0.221	0.088	0.442	0.037	0.261	1.453
Condiments	1.38%	0.980	0.127	0.127	0.000	0.853	0.108	0.150	1.688
Eggs	0.93%	0.000	0.109	0.000	0.109	0.000	0.000	0.000	0.000
Salad Dressing	2.72%	1.000	0.164	0.164	0.000	0.836	0.115	0.250	3.119
Snack food	4.60%	0.998	0.764	0.762	0.002	0.236	0.167	0.356	5.939
Coffee & Tea	1.51%	0.909	0.073	0.073	0.000	0.836	0.101	0.123	1.302
Oral Care	0.51%	0.966	0.055	0.055	0.000	0.911	0.107	0.205	2.323
Refrigerated Juices	4.88%	1.000	0.927	0.927	0.000	0.073	0.162	0.286	4.699
Paper Goods	2.80%	1.000	0.927	0.927	0.000	0.073	0.223	0.158	3.513
Frozen & Canned Seafood	1.82%	0.739	0.636	0.467	0.170	0.272	0.038	0.242	1.324
Fresh Seafood	0.74%	0.110	0.473	0.082	0.391	0.028	0.014	0.044	0.576
Laundry Detergents & Fabric Softeners	1.37%	1.000	0.709	0.709	0.000	0.291	0.344	0.140	4.892
Pasta	1.84%	0.994	0.109	0.109	0.000	0.885	0.063	0.328	2.110
Yogurt	1.08%	0.366	0.073	0.043	0.030	0.323	0.036	0.133	1.283

TABLE 5: AGGREGATE – AGGREGATE ANALYSIS (MODEL 1)

Independent Variable	Dependent Variable					
	Log (Traffic)		Log (Sales/Traffic)		Log (Profit/Sales)	
	Estimate	t Value	Estimate	t Value	Estimate	t Value
Intercept	7.4988	26.75	2.7637	33.84	-0.6008	-8.79
Pct. categories featured	0.0000	0.01	-0.0001	-0.11	-0.0042	-3.79
Pct. competitor categories featured	-0.0011	-1.77	-0.0019	-2.69	-0.0050	-4.31
AD for non loss leaders*	0.0287	1.79	0.0173	0.93	0.0288	4.00
AD for loss leaders*	0.1130	4.67	0.0296	1.09	-0.0616	-5.69
Temperature	-0.0008	-3.23	-0.0005	-1.76	-0.0005	-1.05
Lagged dependent variable	0.1796	5.74	-0.0621	-2.20	0.2438	5.48
Plus holiday effects						
Plus store effects						
R-Squared	0.9600		0.8656		0.4219	
Sample Size	1296		1296		1296	

* Measured on a log scale in traffic and sales equations.

Independent Variable	Dependent Variable					
	Log (Traffic)		Log (Sales/Traffic)		Log (Profit/Sales)	
	Estimate	t Value	Estimate	t Value	Estimate	t Value
Intercept	6.9903	21.84	3.1144	17.89	-0.5504	-5.38
Pct. categories featured	-0.0013	-3.38	0.0012	2.75	0.0027	3.33
Pct. competitor categories featured	-0.0005	-0.84	-0.0025	-3.48	-0.0084	-6.51
AD for non loss leaders*	0.0693	3.48	-0.0209	-0.88	-0.0412	-3.60
Breadth Loss Leaders*	0.1841	5.55	-0.0508	-1.36	-0.0784	-10.62
Depth Loss Leaders*	-0.0185	-0.51	0.1080	2.54	0.0170	5.30
Temperature	-0.0011	-4.31	-0.0002	-0.69	0.0015	2.79
Lagged dependent variable	0.2024	6.40	-0.0831	-2.79	0.2110	4.95
Plus holiday effects						
Plus store effects						
R-Squared	0.9589		0.8647		0.4126	
Sample Size	1296		1296		1296	

* Measured on a log scale in traffic and sales equations.

TABLE 6: AGGREGATE – DISAGGREGATE ANALYSIS (MODEL 2)*

Independent Variable	Dependent Variable					
	Log (Traffic)		Log (Sales/Traffic)		Log (Profit/Sales)	
	Estimate	t Value	Estimate	t Value	Estimate	t Value
Intercept	5.9429	21.56	2.2111	17.74	-0.5365	-5.92
Competitor Feature Meat	-0.0044	-0.54	-0.0719	-6.13	0.0085	0.58
Competitor Feature Ice Cream	-0.0296	-3.23	-0.0768	-6.91	0.0054	0.37
Competitor Feature Soft Drinks	-0.0324	-3.48	-0.0382	-4.83	-0.0022	-0.14
Competitor Feature Cereal	0.0000	.	-0.0703	-7.58	0.0165	1.29
Competitor Feature Frozen/Canned Fruit/Veg	-0.0667	-5.26	-0.0382	-4.54	0.0620	5.25
Competitor Feature Cheese	-0.1326	-9.81	-0.0418	-2.52	0.0613	2.10
Competitor Feature Soup	-0.1498	-5.45	-0.1282	-4.48	0.0060	0.50
Competitor Feature Milk	-0.0258	-3.73	0.0000	.	-0.0895	-3.66
Competitor Feature Salad Dressing	0.0000	.	-0.0385	-3.70	-0.0374	-3.56
Competitor Feature Snack food	-0.0018	-0.24	0.0000	.	-0.0917	-5.80
Competitor Feature Refrigerated Juices	-0.0716	-12.47	-0.0371	-4.72	-0.0306	-2.84
Competitor Feature Paper Goods	-0.0370	-7.91	-0.0041	-0.67	0.0692	7.83
Competitor Feature Laundry Items	-0.0003	-0.04	0.0000	.	0.0074	0.69
Competitor Feature Pasta	-0.0467	-3.53	-0.0453	-5.23	-0.0935	-7.70
Competitor Feature Yogurt	0.0000	.	-0.0111	-1.03	0.0476	2.47
Temperature	-0.0015	-3.68	-0.0047	-9.07	0.0025	3.11
Lagged Dependent Variable	0.3628	12.13	0.0407	1.40	0.0739	2.22
AD LL Meat	0.0285	3.40	0.0000	.	-0.0267	-4.08
AD LL Produce	0.0463	6.78	0.0253	2.92	-0.0557	-9.11
AD LL Ice Cream	0.0000	.	0.0518	3.46	-0.0032	-1.25
AD LL Beer	0.0121	1.73	0.0070	0.91	-0.0483	-15.71
AD LL Prepared Foods	0.0117	2.44	0.0262	2.70	0.0000	.
AD LL Cereal	0.0145	3.66	0.0000	.	0.0000	.
AD LL Frozen or Canned Fruits/Veggies	0.0000	.	0.0074	0.88	0.0000	.
AD LL Cheese	0.0223	1.96	0.0344	3.32	0.0000	.
AD LL Beauty Care	0.0000	.	0.0223	2.55	-0.0317	-8.00
AD LL Spreads	0.0039	0.48	0.0082	1.32	-0.0168	-6.26
AD LL Condiments	0.0456	7.57	0.0000	.	-0.0159	-3.13
AD LL Coffee & Tea	0.0681	3.22	0.0000	.	-0.0194	-2.81
AD LL Frozen/Canned Seafood	0.0086	1.50	0.0000	.	-0.0138	-2.94
AD LL Fresh Seafood	0.0282	5.92	0.0095	1.65	-0.0239	-8.91
AD LL Pasta	0.0101	1.83	0.0585	6.71	-0.0372	-12.04
AD NL Produce	0.0000	.	0.0150	1.94	-0.0008	-7.08
AD NL Carbonated soft drinks	0.0000	.	0.0616	5.40	-0.0074	-2.76
AD NL Beer	0.0114	2.14	0.0000	.	-0.0175	-4.52
AD NL Prepared Foods	0.0009	0.17	0.0000	.	0.0000	.
AD NL Frozen or Canned Fruits/Veggies	0.0000	.	0.0203	2.81	0.0000	.
AD NL Cheese	0.0071	1.27	0.0034	0.67	-0.0162	-9.48
AD NL Bakery products	0.0000	.	0.0477	2.31	-0.0358	-3.41
AD NL Beauty Care	0.0077	1.43	0.0000	.	-0.0002	-0.03
AD NL Spreads	0.0387	5.15	0.0000	.	0.0000	.
AD NL Snack food	0.0000	0.01	0.0725	4.51	-0.0264	-6.71
AD NL Oral Care	0.0428	4.60	0.0000	.	-0.0110	-3.38
AD NL Yogurt	0.0000	.	0.0271	4.68	-0.0007	-0.36
Plus holiday effects						
Plus store effects						
R-Squared	0.9762		0.8934		0.8140	
Sample Size	1296		1296		1296	

* AD is measured on a log scale in traffic and sales equations. In the traffic equation it is interacted with presence or absence of feature in category. AD LL refers to AD for loss leaders; AD NL refers to AD for non-loss leader promotions. Zero values of coefficients indicate that constraints on signs of coefficients were binding. Excluded categories for AD had zero coefficients in sales and traffic equations.

TABLE 7: PROFITABILITY ANALYSIS BASED ON MODELS 1 AND 2

Category	AD	Log Actual - Log No Loss Leaders				Sum	Std. Dev. of Sum	t = Sum/Std. Dev.	Profit LL/ Profit no LL
		Traffic	Sales	Margin	Sum				
Model 1	3.237	0.163	0.043	-0.199	0.007	0.035	0.192	1.007	
Model 2									
<i>Meat</i>	0.817	0.017	0.000	-0.022	-0.005	0.007	-0.655	0.995	
<i>Produce</i>	0.814	0.028	0.015	-0.045	-0.003	0.008	-0.320	0.997	
<i>Ice Cream</i>	9.657	0.000	0.122	-0.031	0.092	0.043	2.120	1.096	
<i>Beer</i>	2.493	0.015	0.009	-0.120	-0.096	0.015	-6.387	0.908	
<i>Prepared Foods</i>	4.518	0.020	0.045	0.000	0.065	0.018	3.507	1.067	
<i>Cereal</i>	3.105	0.020	0.000	0.000	0.020	0.006	3.661	1.021	
<i>Frozen or Canned Fruits/Veggies</i>	1.246	0.000	0.006	0.000	0.006	0.007	0.875	1.006	
<i>Cheese</i>	1.047	0.016	0.025	0.000	0.041	0.011	3.674	1.041	
<i>Beauty Care</i>	2.608	0.000	0.029	-0.083	-0.054	0.015	-3.545	0.947	
<i>Spreads</i>	1.453	0.004	0.007	-0.024	-0.014	0.010	-1.354	0.987	
<i>Condiments</i>	1.688	0.045	0.000	-0.027	0.018	0.010	1.745	1.018	
<i>Coffee & Tea</i>	1.302	0.057	0.000	-0.025	0.031	0.020	1.593	1.032	
<i>Frozen/Canned Seafood</i>	1.324	0.007	0.000	-0.018	-0.011	0.008	-1.400	0.989	
<i>Fresh Seafood</i>	0.576	0.013	0.004	-0.014	0.003	0.004	0.904	1.003	
<i>Pasta</i>	2.110	0.011	0.066	-0.079	-0.001	0.013	-0.061	0.999	
Category	AD	Log Optimal - Log No Loss Leaders				Sum	Std. Dev. of Sum	t = Sum/Std. Dev.	Profit LL/ Profit no LL
		Traffic	Sales	Margin	Sum				
Model 1	1.317	0.095	0.025	-0.081	0.039	0.025	1.545	1.040	
Model 2									
<i>Meat</i>	0.067	0.002	0.000	-0.002	0.000	0.001	0.084	1.000	
<i>Produce</i>	0.287	0.012	0.006	-0.016	0.002	0.003	0.638	1.002	
<i>Ice Cream</i>	15.173	0.000	0.144	-0.049	0.095	0.057	1.678	1.100	
<i>Beer</i>	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	
<i>Beauty Care</i>	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	
<i>Spreads</i>	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	
<i>Condiments</i>	1.865	0.048	0.000	-0.030	0.018	0.011	1.605	1.018	
<i>Coffee & Tea</i>	2.506	0.085	0.000	-0.049	0.037	0.032	1.162	1.037	
<i>Frozen/Canned Seafood</i>	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	
<i>Fresh Seafood</i>	0.576	0.013	0.004	-0.014	0.003	0.004	0.904	1.003	
<i>Pasta</i>	0.840	0.006	0.036	-0.031	0.011	0.007	1.544	1.011	